SCIENTIFIC OASIS

Decision Making Advances

Journal homepage: www.dma-journal.org
ISSN: 2956-2384

Performance Analysis of Indian Railway Zones using MCDM Approaches

Soumyadeep Ganguly[1,*], Sugata Ray Chaudhury[1], Abheek Mukherjee[1], Amalendu Si[1]

[1] Information Science, Maulana Abul Kalam Azad University of Technology, West Bengal, India

ARTICLE INFO

Article history:
Received 7 June 2024
Received in revised form 15 September 2024
Accepted 9 October 2024
Available online 18 October 2024

Keywords:
MCDM; Indian Railways; Supply and demand; Data analysis.

ABSTRACT

The study aims to enhance the efficiency and effectiveness of Indian Railways (IR), a public sector infrastructural organization, through a performance analysis using various Multi-Criteria Decision-Making (MCDM) methods. Analyzing the Indian Railway's open data, the study optimizes and ranks the zones of IR, offering insights for targeted investments to boost future performance. This research holds value by furnishing managerial perspectives, formulating strategies, and elevating the performance of different zones within Indian Railways. Through the identification of improvement areas, the analysis empowers decision-making, facilitating overall enhanced performance. MCDM, Indian Railways, Supply and demand, Data analysis.

1. Introduction

The principal role of transportation is to provide or improve access to different location for business and individuals, for both freight and personal travels. Roads and railways are the country of India's modern modes of transportation. In the case of railway's, it's controlled by The Indian Railway's (IR). There is increasing pressure on it to address the lack of customer orientation and to fully realize the scope of its assets through effective system and technological use [1]. Therefore, a system to analyze the procurement of each zone in the IR and assign them a proper positional rating is essential.

The administration and control of businesses that provide infrastructure for the public sector are becoming more and more dependent on performance analysis. The primary goals of performance measurement in the public sector are to strengthen accountability so that organizations are held fully responsible for the resources they use and the results they produce, as well as to enhance economy and effectiveness in service delivery [2]. Its position as one of the key sectors of the Indian economy has been strengthened further by the sector's rapid growth over the past few years. In India, the service sector presently makes up more than 60% of the country's GDP [3]. By developing

* *Corresponding author.*
E-mail address: soumyadeepganguly1922@gmail.com

https://doi.org/10.31181/dma31202549

infrastructure to support 45% of the economy's contribution to modal freight, India's railway industry hopes to add 1.5% to the GDP of the nation [3].

MCDM, constitutes a pivotal approach to make the decision. It strives to identify the optimal choice by factoring in multiple criteria during the selection process. Offering a diverse array of tools and methods, MCDM finds utility across various domains, spanning from finance to engineering design. Among all MCDM method, TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), VIKOR (Vlse Kriterijumska Optimizacija Kompromisno Resenje), PROMETHEE II and COPRAS (Complex Proportion Assessment) are used in this paper for Ranking analysis.

The remainder of the paper is structured as follows: Previous works are briefly reviewed in section 2. The section 3 includes some basic information about Indian Railways after that. The section 4 describes the suggested methodology. The work's key conclusions are offered in section 6 after the data results and discussion are presented in section 5 of the final report.

2. Literature Review

We analyze research that compare the overall effectiveness of several Indian Railway zones using quantitative methods. Agarwal [4] conducted a survey involving 500 participants to ascertain the primary factors contributing to customer satisfaction in the field of Industrial Relations. The findings revealed that employee behavior emerged as the most significant factor in enhancing customer satisfaction. Abraham George and Rangaraj [1] conducted an evaluation of IR's zones by employing the DEA methodology. Their objective was to examine operations related to IR from a supply chain perspective in order to gain fresh insights [1]. They make use of information from the IR Annual statistical reports. The study not only acknowledged the performance of the zones but also facilitated the formulation of strategies by the leadership to enhance zonal performance. Singh [5] conducted an assessment of the Kolkata Metro Railway's performance and put forth a range of recommendations aimed at enhancing its viability and profitability. In addition to other sensible suggestions, it was urged that a single Metropolitan Transport Authority be established to manage all kinds of transportation. Raghuram and Gangwar [6] conducted a comprehensive examination of the matters concerning financial and physical aspects associated with revenue generation from freight and passenger traffic within the Indian Railways. The study spanned the period from 1987 to 2007 [6]. In order to evaluate and analyze the performance of sixteen IR zones, Ranjan *et al.,* [3] integrated the DEMATEL and VIKOR approaches and created a multi-criteria decision-making framework. The Western zone is ranked first while the North-Eastern zone is last in the data, which is gathered from a number of sources including the annual IR statistical report from past years. There are nine criteria used to analyse the performance of zones, however none of them are intangible, leaving out several crucial performance elements of railway zones like passenger comfort. A summary of all works are provided in Table 1.

Table 1
Summary of Literature Review

References	Area(s) covered
Ranjan *et al.,* [3]	Evaluation of the 16 IR zones' performance
Agarwal [4]	Greatest effect on client satisfaction in IR
Abraham George and Rangaraj [1]	Evaluation of the IR zones' operational effectiveness
Raghuram and Gangwar [6]	The problem of generating money from traffics
Singh [5]	Evaluation of Kolkata Metro's performance

3. About Indian Railways

Indian Railways (IR) is a governmental organization under the jurisdiction of the Ministry of Railways, Government of India. It oversees the world's fourth-largest railway network in terms of size, encompassing a total route length of 68,043 kilometers (42,280 miles), a running track length of 102,831 kilometers (63,896 miles), and an overall track length of 128,305 kilometers (79,725 miles) as of March 31, 2022. Additionally, as of April 1, 2022, a significant portion of the railway network, measuring 50,394 kilometers (31,313 miles), has been electrified and utilizes 25 kV 50 Hz AC electric traction. In 2020, Indian Railways transported a staggering 8.086 billion passengers, and by 2022, it had moved an impressive 1,418.1 million tons of freight. The extensive railway network comprises 13,169 daily passenger trains, servicing both long-distance and suburban routes, and connecting a network of 7,325 stations across India.

The Mail or Express trains, which run the most often, maintain an average speed of 50.6 km/h. Passenger trains travel at an average speed of 33.5 km/h, while suburban EMUs operate at a slightly slower average speed of 37.5 km/h.

Indian Railways runs an astounding 8,479 freight trains every day at an average speed of about 42.2 km/h. Depending on their axle load, freight trains can travel at a top speed of 60 to 75 km/h. The top speed of "container special" trains is 100 km/h.

Indian Railways has an excellent fleet of rolling stock as of March 2020, which included 12,729 locomotives, 76,608 passenger coaches, and 293,077 freight wagons. The company owns production facilities for locomotives and coaches spread out across India. It ranks as the fourteenth-largest employer in the world as of March 2020 with 1.254 million employees.

4. Methodology

We have collected some open data on all the IR zones (Table 2), about their expenditure and incomes. In our dataset all the data about all gauges (BG, MG and NG) is present. There is total 32 rows (all zones) and 68 criterion. Among the thirty two zones there are total sixteen Broad-Gauge(BG) zones. During the last ten years Indian Railway has stopped usages of MG and NG routes, therefore, maximum data about those zones are missing. So, we dropped all the rows of the dataset which containing MG and NG information. Within the dataset of the Broad-Gauge railway contains some missing data, so all those missing data are replaced using the statistical approaches such as mean and standard deviation according to the types of the criteria. After dealing with missing data on the dataset, we faced outliers in several features. Here we used Inter Quartile Range (IQR) Method to detect and remove the outliers. Workflow of the proposed framework is presented on Figure 1.

Table 2
Few details of all IR zones

Name	Establishment Year	Headquarter
Central (CR)	1951	Delhi
Eastern (ER)	1952	Kolkata
East Central (ECR)	2002	Hazipur
East Coast (ECOR)	2003	Bhubaneswar
Northern (NR)	1952	Delhi
North Central (NCR)	2003	Allahabad
Northeastern (NER)	1952	Gorakhpur
North Frontier (NFR)	1958	Guwahati
Northwestern (NWR)	2002	Jaipur
Southern (SR)	1951	Chennai

Name	Establishment Year	Headquarter
South Central (SCR)	1966	Secundrabad
South Eastern (SER)	1955	Kolkata
South East Central (SECR)	2003	Bilaspur
Western(WR)	1951	Mumbai
West Central (WCR)	2003	Jabalpur
South Western (SWR)	2003	Hubballi

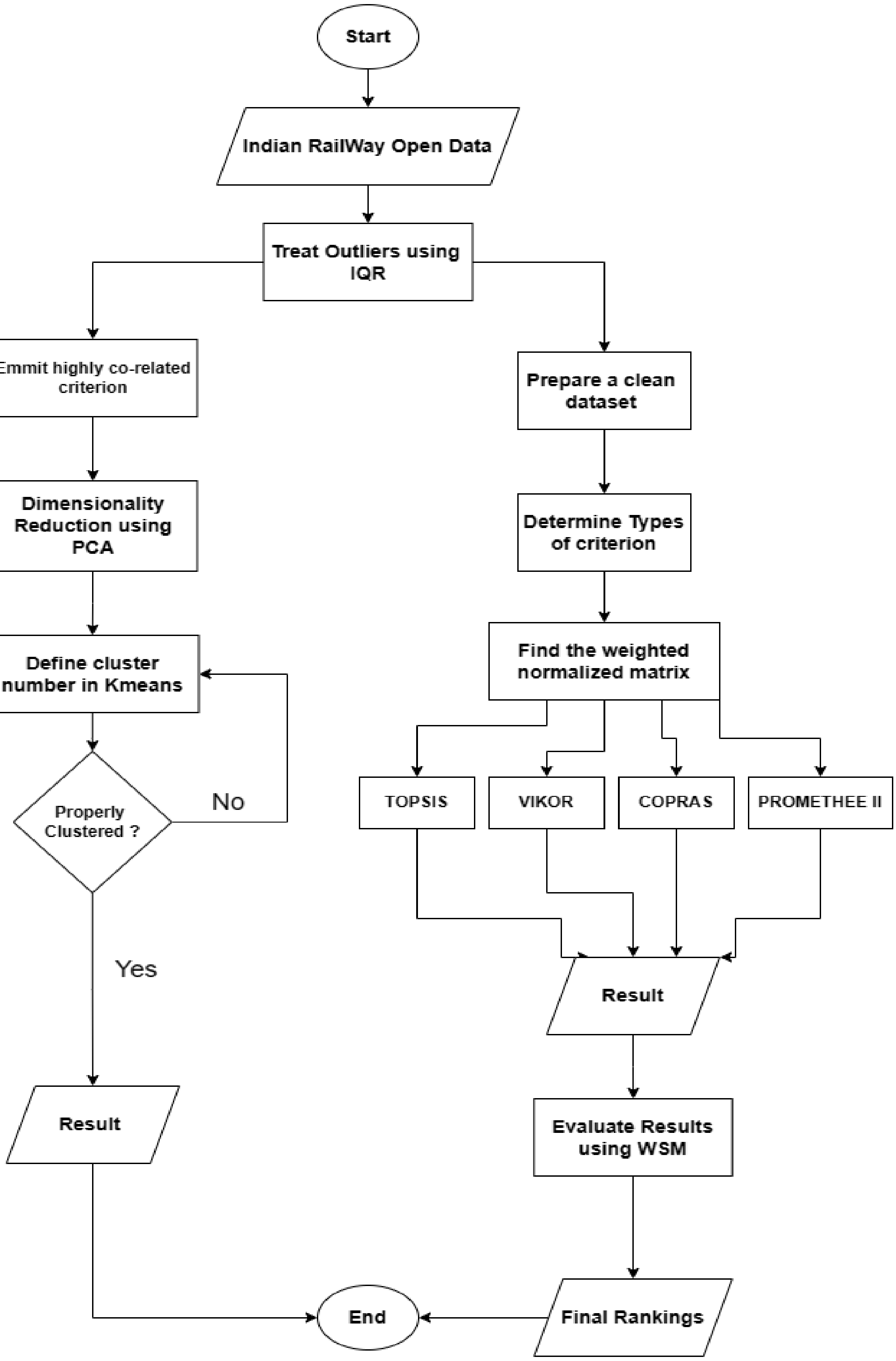

Fig. 1. Workflow

After That Principal Component Analysis and K-means are performed, all this are done using python programming language, and then the MCDMs are performed to get more accurate rankings.

4.1 Dimensionality reduction and K-means

Lot of criteria means high dimensionality in the data set, which is inappropriate for error free analysis. Therefore, we must choose effective criteria. Despite choosing criteria on guess, we use Principal Component Analysis (PCA) to reduce high dimension and extract new features [7]. Before applying the PCA, we calculate the correlation between the attributes. And, we dropped all those criteria, are correlated to others, manually, which are more than 90 percentile correlated to each other.

After this, we have performed PCA and calculate the Explained Variance Ratio and Cumulative Variance Ratio.

Table 3
Cumulative Variance of all principal components

0.50143	0.69716	0.83150	0.91470	0.95042
0.98060	0.99057	0.99537	0.99855	1.0

According to this cumulative variance in Table 3, first six principal component has gathered approx. 98 percentile (red line) of actual features. These features can be used for plotting all data points. Visualize the cumulative variance and individual variance in Figure 2.

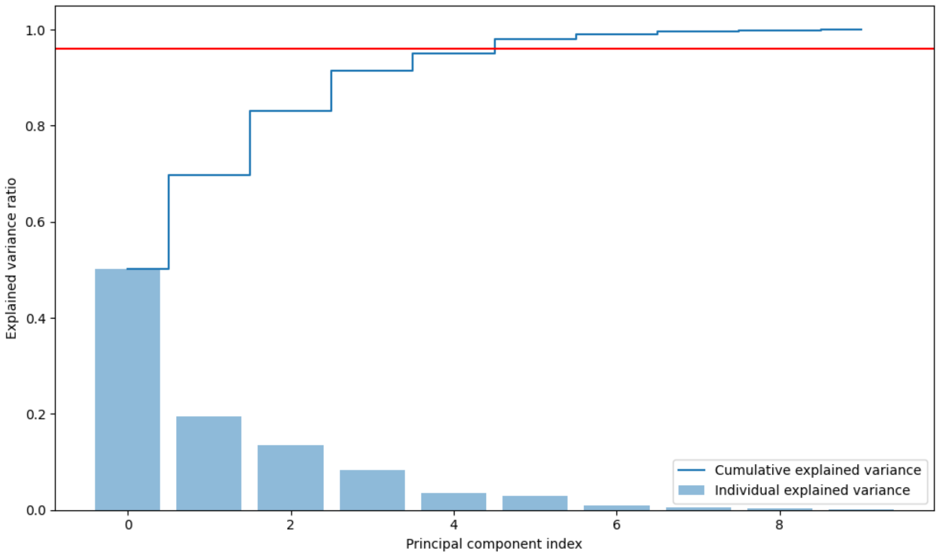

Fig. 2. Scree Plot of all cumulative variances with 0.98 threshold(red line)

K-means clustering [8] is used to classify all zones according to their performance. Three class of clusters are defined,i.e. Worst, Moderate and Good (Table 4).

But, it’s a assumption based study. From this we can’t say that which is the best performing zone. Therefore, for more accurate rankings we need to follow some other approaches considering large data-sets.

Table 4
Performance Result of Kmeans Clustering of all IR Zones

IR Zones	Performance
CR	Worst
ER	Moderate
ECR	Moderate
ECOR	Moderate
NR	Moderate
NCR	Worst
NER	Moderate
NFR	Moderate
NWR	Worst
SR	Moderate
SCR	Moderate
SER	Moderate
SECR	Good
WR	Good
WCR	Moderate
SWR	Moderate

4.2 Interquartile Range

The Interquartile Range (IQR) is a statistical measure used to assess the spread or the dataset while mitigating the impact of outliers [7]. It focuses on the central 50 percentile of the data, providing valuable insights into the variability within that range. To compute the IQR, the dataset is divided into four quartiles: Q1, Q2 (median), and Q3. Q1 corresponds to the 25th percentile, Q2 to the 50th percentile (also known as the median), and Q3 to the 75th percentile. The IQR is calculated as the difference between Q3 and Q1.

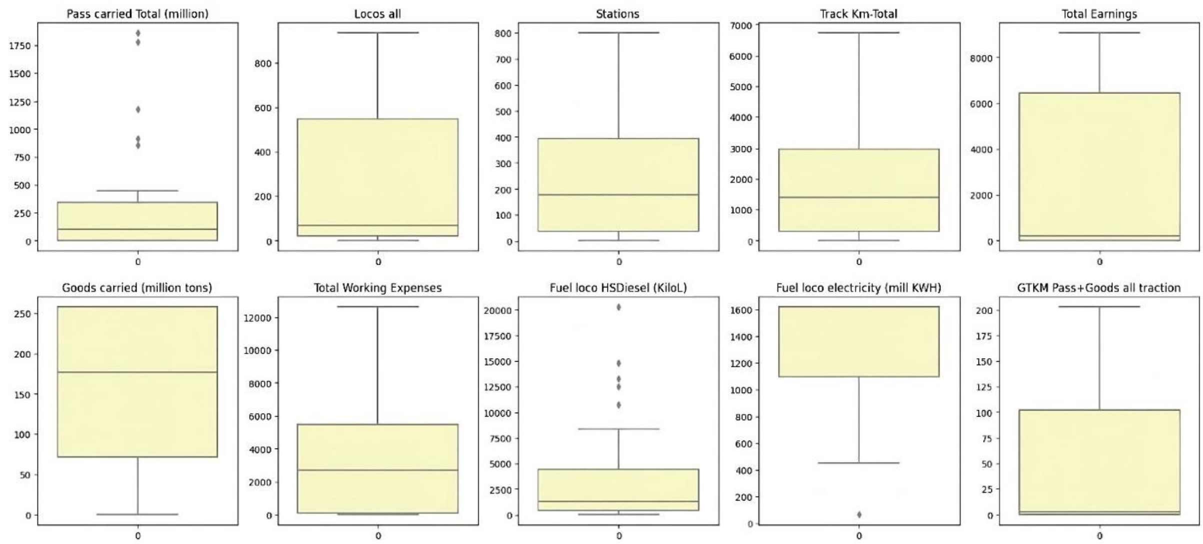

Fig. 3. Before removing outliers from all the criterion

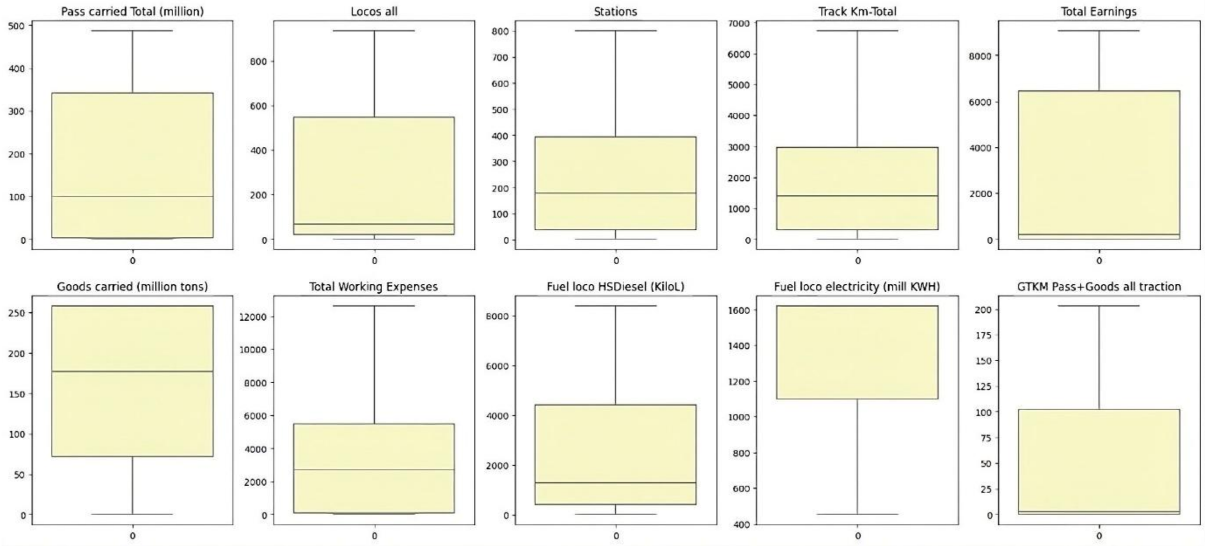

Fig. 4. After removing outliers from all the criterion

In Figure 3 and Figure 4, we've chosen a row and plotted a boxplot, and we can see in Figure 4 that there are some dots on the higher bound and some on the lower bound, which are the outliers. And in Figure 5, we can see that there are no dots, which signifies that there are no outliers. We have replaced the outliers with mean values so that we may reach our conclusion quickly and without any external interference.

4.3 MCDM Approaches

Multi-Criteria Decision Making (MCDM) techniques are used to make decisions when there are multiple, often conflicting, criteria to consider. MCDM techniques can be used to rank or choose between alternatives, or to identify the best compromise solution. The choice of MCDM technique depends on the specific decision problem being solved. However, all MCDM techniques can be helpful in making decisions when there are multiple, often conflicting, criteria to consider. For various compelling reasons, we selected to use Multi-Criteria Decision-Making (MCDM) methodologies in our work. MCDM is quite valuable in our study since it allows you to systematically evaluate and rate the performance of various Indian Railways zones using a variety of criteria. Given the complexity and diverse nature of performance analysis, MCDM provides a systematic framework for simultaneously considering multiple elements such as expenditure, revenue, and other criteria that influence efficiency and effectiveness.

We can use MCDM methods to analyse our 10 selected criteria, allowing for a more extensive analysis that goes beyond simple linear comparisons. We can properly balance the value of each criterion, analyse trade-offs, and arrive at well-informed rankings by using approaches such as TOPSIS, VIKOR, COPRAS and PROMETHEE II.

Here, the analysis of all MCDM methods are based on decision matrix D, which is represented in Eq. (1)

$$D = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1j} \\ X_{21} & X_{22} & \cdots & X_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ X_{i1} & X_{i2} & \cdots & X_{ij} \end{bmatrix} \tag{1}$$

4.3.1 TOPSIS method

The TOPSIS method was initially formulated by Hwang and and Yoon in 1981 [9]. The main concept behind this technique is to select a solution that is the close to the positive ideal solution while also being the furthest away from the negative ideal solution. Compared to the negative ideal solution, which tries to maximize the conflicting criteria while reducing the beneficial criteria, the positive ideal solution seeks to maximize benefit criteria [10,11]. The step by step procedure of TOPSIS is given bellow:

Step 1. Using the decision matrix (D), create the normalized decision matrix using the following formula:

$$X_{ij}^* = \frac{x_{ij}}{\sqrt{\sum x_j^2}} \tag{2}$$

Step 2. To determine the weights for each attribute, considering their relative importance, use above equation. Summation of these weights should equal to 1, thus assigning equal importance to all criteria.

$$W_i = \frac{V_j}{\Sigma \mathrm{V_j}}, \Sigma \mathrm{W_j} = 1 \tag{3}$$

where V_j is each attribute's variance, which is determined using the formula provided, as

$$V_j = \frac{1}{n} \sum (X_i^* - (X_i^*)_m)^2 \tag{4}$$

Step 3. Using W_j and all the values X_{ij}^*, multiply to get the weighted Normalized Matrix V_{ij}^*, such as,

$$V_{ij} = W_j . X_i \tag{5}$$

$$V_{ij}^* = \begin{bmatrix} V_{11} & V_{12} & \cdots & V_{1j} \\ V_{21} & V_{22} & \cdots & V_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ V_{i1} & V_{i2} & \cdots & V_{ij} \end{bmatrix} \tag{6}$$

Step 4. This step determines positive ideal (best) solution and negative ideal (worst) solutions. The positive ideal and negative ideal solution given as.

a) The Ideal Solution:

Maximum value of beneficial criteria or minimum value of non-beneficial criteria which is denoted by (V_i^+)

b) Negative Ideal-Solution:

Minimum value of beneficial criteria or maximum value of non-beneficial criteria which is denoted by (V_i^-)

Step 5. Obtain separation (distance) of each alternative from the ideal solution and negative ideal solution which is given by the Euclidean distance given by the equations.

$$D_i^+ = \sqrt{\sum (V_{ij} - V_j^+)^2}, i = 1, \ldots, n \tag{7}$$

$$D_i^- = \sqrt{\sum (V_{ij} - V_j^-)^2}, i = 1, \ldots, n \tag{8}$$

Step 6. Determine how near each option is to the optimal answer using the following formula.

$$C_i^* = \frac{D_i^-}{D_i^+ + D_i^-}, i = 1, \ldots, n \tag{9}$$

Step 7. For each possibility, a set of values is generated. Select the one that comes the closest to the optimum solution. Arrange the alternative following a decreasing order of C_i^*.

4.3.2 VIKOR method

VIKOR, commonly referred to as the compromise ranking method, is an approach that identifies a potential solution which is nearest to the best solution [13]. The term 'compromise' in this context signifies an agreement reached through mutual concessions [3]. The step by step procedure of VIKOR is given bellow:

Step 1. Find the weighted normalized matrix for VIKOR using decision matrix D. Following the formula given bellow,

$$V_{ij} = W_j \frac{f_i - f_j^+}{f_j^+ + f_j^-} \tag{10}$$

$$V_{ij}^* = \begin{bmatrix} V_{11} & V_{12} & \cdots & V_{1j} \\ V_{21} & V_{22} & \cdots & V_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ V_{i1} & V_{i2} & \cdots & V_{ij} \end{bmatrix} \tag{11}$$

Step 2. Determine the utility and regret factor for each alternatives.

$$S_i = \sum W_{ij} \frac{f_i - f_j^+}{f_j^+ + f_j^-} \tag{12}$$

$$R_i = \max(W_{ij} \frac{f_i - f_j^+}{f_j^+ + f_j^-}) \tag{13}$$

Step 3. For each alternative, determine the VIKOR index value expressed as follows.

$$Q_i = v \frac{S_i - S^+}{S^+ + S^-} + (1 - v) \frac{R_i - R^*}{R^- - R^*} \tag{14}$$

where (1 - v) is the weight of the individual regret, and v is the weight value for the max value of group utility. Usually, v is set to 0.5.

Step 4. By looking at the Q_i value, one can rank the possibilities. A greater quality can be determined by a lower value.

4.3.3 COPRAS method

The COPRAS method is, in essence, a normalization technique that amalgamates all indicators into a unified quantitative measure, represented by the method criterion's value [14]. The step by step procedure of COPRAS is given bellow:

Step 1. Develop the Weighted normalized decision matrix based on decision matrix D. Where W_j (j = 1, 2, ..., n) is the weight of all criterion.

$$V_{ij} = W_j \frac{X_{ij}}{\sum X_{ij}} \tag{15}$$

$$V_{ij}^* = \begin{bmatrix} V_{11} & V_{12} & \cdots & V_{1j} \\ V_{21} & V_{22} & \cdots & V_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ V_{i1} & V_{i2} & \cdots & V_{ij} \end{bmatrix} \tag{16}$$

Step 2. Sum of Weighted normalized decision matrix :

$$S_i^+ = \sum V_{ij}^+ \tag{17}$$

$$S_i^- = \sum V_{ij}^- \tag{18}$$

Step 3. Analyze the relative importance of the various alternatives.

$$Q_i = S_i^+ + \frac{S_{min}^- \sum S_i^-}{S_i} \sum \frac{S_{min}^-}{S_i^-} \quad (19)$$

(i = 1,2,3,.....m) where

$$S_{min}^- = S_i^- \quad (20)$$

Step 4. Calculative the quantitative utility.

$$U_i = \frac{Q_i}{Q_{max}} X100 \quad (21)$$

Higher utility is the best alternative.

4.3.4 PROMETHEE II

The step by step procedure of PROMETHEE II is given bellow [15,16]:

Step 1. Normalize the decision matrix D.

For beneficial criteria:

$$X_i = \frac{f_i - f_j^-}{f_j^+ + f_j^-} \quad (22)$$

For non-beneficial criteria:

$$X_i = \frac{f_j^+ - f_i}{f_j^+ + f_j^-} \quad (23)$$

Weighted Normalized Matrix will be,

$$V_{ij} = W_j X_i \quad (24)$$

$$V_{ij}^* = \begin{bmatrix} V_{11} & V_{12} & \cdots & V_{1j} \\ V_{21} & V_{22} & \cdots & V_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ V_{i1} & V_{i2} & \dots & V_{ij} \end{bmatrix} \quad (25)$$

Step 2. Sum of Weighted normalized decision matrix :

$$S_i^+ = \sum V_{ij} \quad (26)$$

$$S_i^- = \sum V_{ij} \quad (27)$$

Step 3. Pairwise comparison to determine the deviation.

$$d_j(a,b) = g_i(a) - g_j(b) \quad (28)$$

The difference between how well a and b performed on each criterion is shown by the notation $d_j(a,b)$.

Step 4. Construct the preference function.

$$P_j(a,b) = F_j[d_j(a,b)] \quad (29)$$

$P_j(a,b)$ is the function of the difference in the assessments of option an in relation to alternative b on each criterion, expressed as a degree from 0 to 1.

Step 5. Determine the multi-criteria preference index

$$\pi(a,b) = \sum P(a,b) W_j \quad (30)$$

Step 6. Determine the positive and the negative outranking flows. Positive outranking flow:

$$\partial^+(a) = \frac{1}{n-1} \sum \pi(a,x) \quad (31)$$

Negative outranking flow:

$$\partial^-(a) = \frac{1}{n-1} \sum \pi(x,a) \quad (32)$$

Step 7. Determine the net flow values, then rank the results.

$$\partial = \partial^{+}(a) - \partial^{-}(a) \tag{33}$$

5. Results Analysis

After getting all the results from different MCDM methods shown in Table 5, there are few dissimilarity have been noticed. The fluctuations of the final outcome can be observed at Figure 5. The final ranking sequence according to TOPSIS, PROMETHEE II and COPRAS are quite similar, but there is a noticeable fluctuation in VIKOR result which is shown in Table 5. The variation of the final ranking occured due to the utilization of different normalisation techniques among the MCDMs. TOPSIS, PROMETHEE II and COPRAS use vector normalisation, where as the VIKOR uses linear normalisation. So, here a comparison of rankings can be performed between VIKOR and TOPSIS or other methods. The final result of VIKOR consider one outcome and another outcome is one of the result of other three MCDMs. In this case, we have choosed the TOPSIS to compare with VIKOR. To check the correlation between the resultant output of TOPSIS and VIKOR, Spearman's Rank Correlation Coefficient (SRCC) is used here [10]. SRCC is calculated using formula bellow.

$$R = 1 - \frac{6\sum d^2}{n^3 - n} \tag{34}$$

where, d is difference of Rank 1 and Rank 2, where as n is number of instances.
Detailed visualisation of Spearman's Rank Correleation is shown in Figure 6.

Table 5
Rankings of IR zones in different MCDM methods

IR Zones	VIKOR	TOPSIS	PROMETHEE II	COPRAS
CR-BG	2	4	5	7
ER-BG	10	13	12	13
ECR-BG	7	11	10	10
ECOR-BG	11	9	8	9
NR-BG	6	6	2	3
NCR-BG	9	3	4	5
NER-BG	16	16	16	16
NFR-BG	15	15	15	15
NWR-BG	13	10	13	12
SR-BG	8	12	11	11
SCR-BG	3	1	1	1
SER-BG	4	7	6	8
SECR-BG	12	8	9	2
SWR-BG	14	14	14	14
WR-BG	1	2	3	4
WCR-BG	5	5	7	6

In Figure 5 worst performance comparison result from all the applied methods are visualized. Here lower value reflects higher ranking and higher value means lower ranking.

In Figure 6 value of Spearman's Correlation Coefficient is 0.81765, the the slope of trade line is positive monotonic or related.

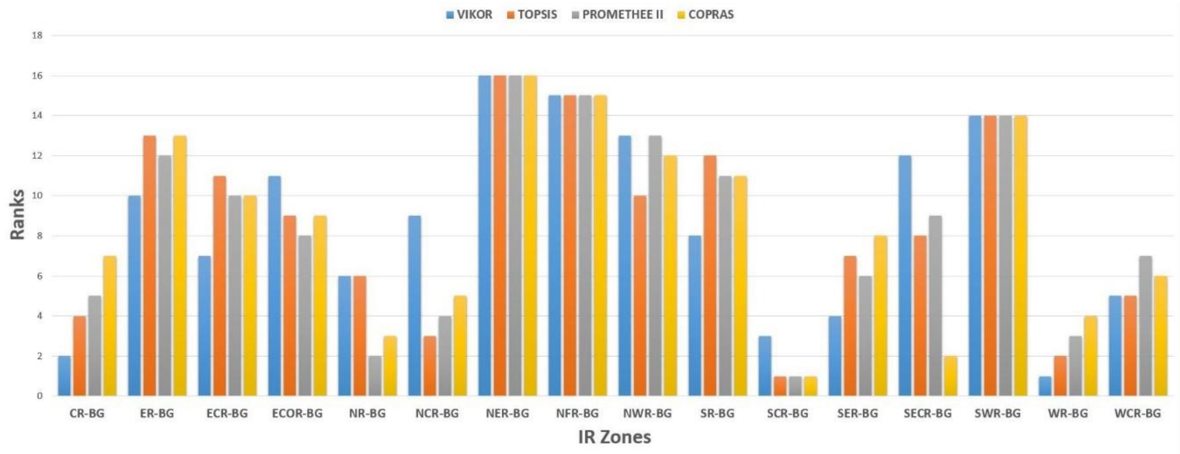

Fig. 5. Comparison of all MCDM rankings

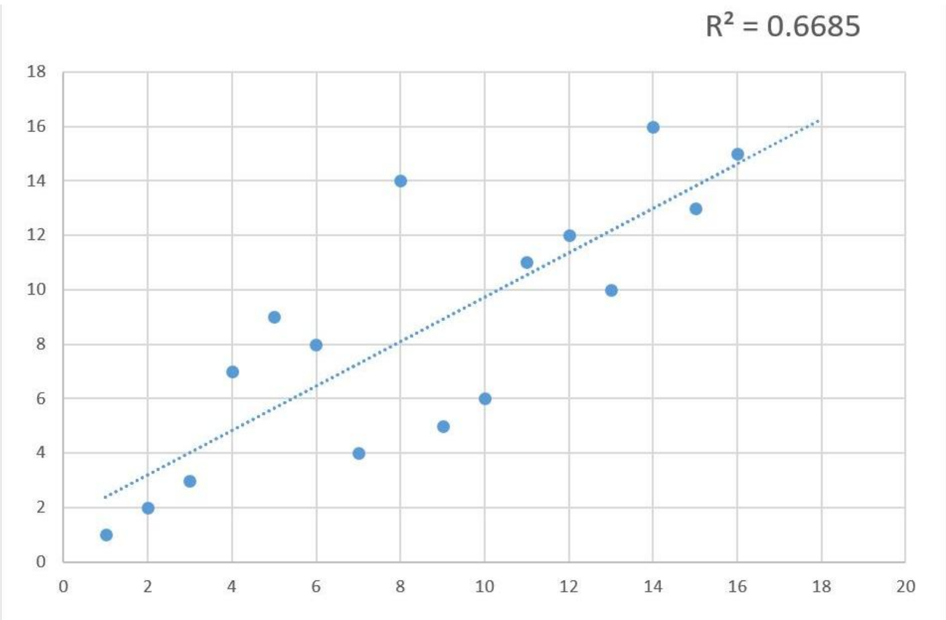

Fig. 6. Spearman's rank correlation chart of VIKOR and TOPSIS rankings

5.1 Weighted sum model (WSM)

The Weighted Sum Model (WSM) is a commonly employed approach, particularly in single-dimensional problems [17]. It is grounded in the assumption of additive utility [18]. While the WSM works well for single-dimensional cases with uniform units, challenges arise when extending it to multi-dimensional Multi-Criteria Decision Making (MCDM) problems [19]. In such scenarios, where diverse dimensions and units come into play, the additive utility assumption breaks down, akin to trying to "add apples and oranges" [11]. To effectively assess the actual ranks, this method could be suitable, as it places all results (in Table 5) from different methods on a comparable scale.

The fundamental principle behind the WSM method involves calculating a weighted sum derived from performance ratings assigned to each alternative across all attributes. The sequential steps for this procedure are outlined as follows:

Step 1. Now, the decision matrix is tab5.Normalise this using Eq. (35).

$$X_{ij}^{*} = 1 - \frac{x_{ij}}{\max X_j} \tag{35}$$

Step 2. Multiply the weight W of individual criterion with their values. In this case all the results has same weightage, which is 0.25.

$$V_{ij}^{*} = W_j X_{ij}^{*} \tag{36}$$

Step 3. Calculate summation of all weighted values for each zones. It is the preference scores of all zone.

$$A_j = \sum V_j^{*} \tag{37}$$

Step 4. Based on preference scores rank all the IR zones accordingly. Higher value will the best.

In Table 6 the final results is displayed. This may be more accurate than the assumption based ranking.

Table 6
Final ranking results, using WSM

IR Zones	Ranks
CR	4
ER	12
ECR	10
ECOR	9
NR	3
NCR	5
NER	16
NFR	15
NWR	12
SR	11
SCR	1
SER	7
SECR	8
SWR	14
WR	2
WCR	6

6. Conclusion

In this study, all the railway zones were benchmarked using several well-known MCDM approaches. While the results of all methods are not identical but, some of them are ranked similarly. This may occur due to the application of equal weights to all criteria. If the weightages are calculated based on the criteria, the results may differ. Nonetheless, the selection of evaluation criteria requires careful consideration, as they hold a pivotal role in assessing performance and subsequently ranking the railway zones. While data sources encompass a variety of criteria, only a limited few are chosen for evaluation, and alternative choices could yield different perspectives. But, those all are tangible criteria; however, the performance of the IR zone may vary when both tangible and intangible criteria are considered. Due to the absence of such data, the results may not be 100 percent accurate in reflecting the actual performance, but they tend to align with the actual performance. This proposed work may be further extended as the future works. Include the additional criteria in the analysis, such as safety and customer satisfaction, to provide a more comprehensive assessment of performance.

Acknowledgement

We would like to express our sincere gratitude to everyone and everyone who contributed to the successful completion of this effort. We would like to extend a special thank you to Dr. Samir Maity, Post Doctorate Fellow, Materials and Production Department, Aalborg University, Denmark, for providing the raw data, intellectual support, inspiring leadership, and tremendous encouragement, suggestions, and cooperation.

Conflicts of Interest

The authors declare no conflicts of interest.

Availability of Data and Materials

All data are collected from Indian Railway open data sources, raw data and other files are https://drive.google.com/drive/folders/1OO8eI5BN72TmHsJptYbWqjPcSj_Xzfqq?usp=sharingattached here.

References

[1] Abraham George, S., & Rangaraj, N. (2008). A performance benchmarking study of Indian Railway zones. Benchmarking: An International Journal, 15(5), 599-617. https://doi.org/10.1108/14635770810903178

[2] Radnor, Z., & McGuire, M. (2004). Performance management in the public sector: fact or fiction?. International journal of productivity and performance management, 53(3), 245-260. https://doi.org/10.1108/17410400410523783

[3] Ranjan, R., Chatterjee, P., & Chakraborty, S. (2016). Performance evaluation of Indian Railway zones using DEMATEL and VIKOR methods. Benchmarking: An International Journal, 23(1), 78-95. https://doi.org/10.1108/BIJ-09-2014-0088

[4] Agarwal, R. (2008). Public transportation and customer satisfaction: the case of Indian railways. Global Business Review, 9(2), 257-272. https://doi.org/10.1177/097215090800900206

[5] Singh, Y. P. (2002). Performance of the Kolkata (Calcutta) Metro Railway: a case study. In urban mobility for all. proceedings of the 10th International CODATU conference. http://worldcat.org/isbn/9058093999

[6] Raghuram, G., & Gangwar, R. (2008). Indian Railways in the past twenty years issues, performance and challenges.

[7] Wan, X., Wang, W., Liu, J., & Tong, T. (2014). Estimating the sample mean and standard deviation from the sample size, median, range and/or interquartile range. BMC medical research methodology, 14, 1-13. https://doi.org/10.1186/1471-2288-14-135

[8] Bock, H. H. (2007). Clustering methods: a history of k-means algorithms. Selected contributions in data analysis and classification, 161-172. https://doi.org/10.1007/978-3-540-73560-1_15

[9] Hwang, C. L., & Yoon, K. (1981). Methods for multiple attribute decision making. Multiple attribute decision making: methods and applications a state-of-the-art survey, 58-191. https://doi.org/10.1007/978-3-642-48318-9_3

[10] Narang, M., Kumar, A., & Dhawan, R. (2023). A fuzzy extension of MEREC method using parabolic measure and its applications. *Journal of Decision Analytics and Intelligent Computing*, *3*(1), 33–46. https://doi.org/10.31181/jdaic10020042023n

[11] Kizielewicz, B., & Sałabun, W. (2024). SITW Method: A New Approach to Re-identifying Multi-criteria Weights in Complex Decision Analysis. Spectrum of Mechanical Engineering and Operational Research, 1(1), 215-226. https://doi.org/10.31181/smeor11202419

[12] Dağıstanlı, H. A. (2024). An Interval-Valued Intuitionistic Fuzzy VIKOR Approach for R&D Project Selection in Defense Industry Investment Decisions. Journal of Soft Computing and Decision Analytics, 2(1), 1-13. https://doi.org/10.31181/jscda21202428

[13] Shekhovtsov, A., & Sałabun, W. (2020). A comparative case study of the VIKOR and TOPSIS rankings similarity. Procedia Computer Science, 176, 3730-3740. https://doi.org/10.1016/j.procs.2020.09.014

[14] Krishankumar, R., Garg, H., Arun, K., Saha, A., Ravichandran, K. S., & Kar, S. (2021). An integrated decision-making COPRAS approach to probabilistic hesitant fuzzy set information. Complex & Intelligent Systems, 7(5), 2281-2298. https://doi.org/10.1007/s40747-021-00387-w

[15] Abedi, M., Torabi, S. A., Norouzi, G. H., Hamzeh, M., & Elyasi, G. R. (2012). PROMETHEE II: A knowledge-driven method for copper exploration. Computers & Geosciences, 46, 255-263. https://doi.org/10.1016/j.cageo.2011.12.012

[16] Abdullah, L., Chan, W., & Afshari, A. (2019). Application of PROMETHEE method for green supplier selection: a comparative result based on preference functions. *Journal of Industrial Engineering International*, *15*, 271-285. https://doi.org/10.1007/s40092-018-0289-z

[17] Chourabi, Z., Khedher, F., Babay, A., & Cheikhrouhou, M. (2019). Multi-criteria decision making in workforce choice using AHP, WSM and WPM. The Journal of The Textile Institute, 110(7), 1092-1101. https://doi.org/10.1080/00405000.2018.1541434

[18] Kaddani, S., Vanderpooten, D., Vanpeperstraete, J. M., & Aissi, H. (2017). Weighted sum model with partial preference information: Application to multi-objective optimization. European Journal of Operational Research, 260(2), 665-679. https://doi.org/10.1016/j.ejor.2017.01.003

[19] Marler, R. T., & Arora, J. S. (2010). The weighted sum method for multi-objective optimization: new insights. Structural and multidisciplinary optimization, 41, 853-862. https://doi.org/10.1007/s00158-009-0460-7

[20] Miljković, B., Žižović, M. R., Petojević, A., & Damljanović, N. (2017). New weighted sum model. Filomat, 31(10), 2991-2998. https://doi.org/10.2298/FIL1710991M